IMPACT OF SEA LEVEL RISE ON DEVELOPMENT SUITABILITY IN NEW YORK CITY

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Abstract

Global climate change and resultant rising sea levels and more frequent flooding are impacting the sustainability and vitality of coastal communities, making identifying vulnerable areas particularly important. Sea level rise projections for the 2020s and 2050s were incorporated into a land use suitability analysis of New York City, which was conducted in a GIS environment based on Ian McHarg's overlay methods. The analytical hierarchy process (AHP) was used to produce weights for the six criteria considered, which were then reclassified and combined according to a weighted linear combination. The results of the suitability analysis suggest that Eastern Staten Island and the southern shore of Brooklyn and Queens are particularly unsuitable for future development. This analysis could be improved by better considering hydrological connectivity when modeling sea level rise.

Introduction

Sea level rise places a significant population at risk. Based on a number of factors, the New York City metropolitan region is particularly vulnerable (Hanson et al. 2011; NPCC 2013; Colle et al. 2008; Bloomfield 1999). Researchers and local and federal decision makers are interested in how a changing climate will affect the area (NYC Department of City Planning 2013a, 2013b; City of New York 2011). As the global climate changes, it is necessary to identify vulnerable areas in order to improve long-term land use planning and disaster relief measures. In this paper, I address these issues through a suitability analysis. I will do such by applying the principles of Ian McHarg's (1969) overlay method to conduct a suitability analysis in a Geographic Information System (GIS) environment to produce a cartographic representation of areas suitable for urbanization and development based on a set of environmental criteria. Including sea level rise as a criterion in the suitability analysis introduces a temporal element that considers how suitability will change in response to global change and will make suitability analysis a more informative tool for decision makers.

I will first review the overarching issues of climate change, sea level rise, New York City's particular vulnerability to sea level rise, and the city's current patterns of development before providing a review of the literature on suitability analysis. I will then detail the data and methods used before discussing the results and implications of this analysis.

Background

Climate Change, Sea Level Rise, and Coastal Vulnerability

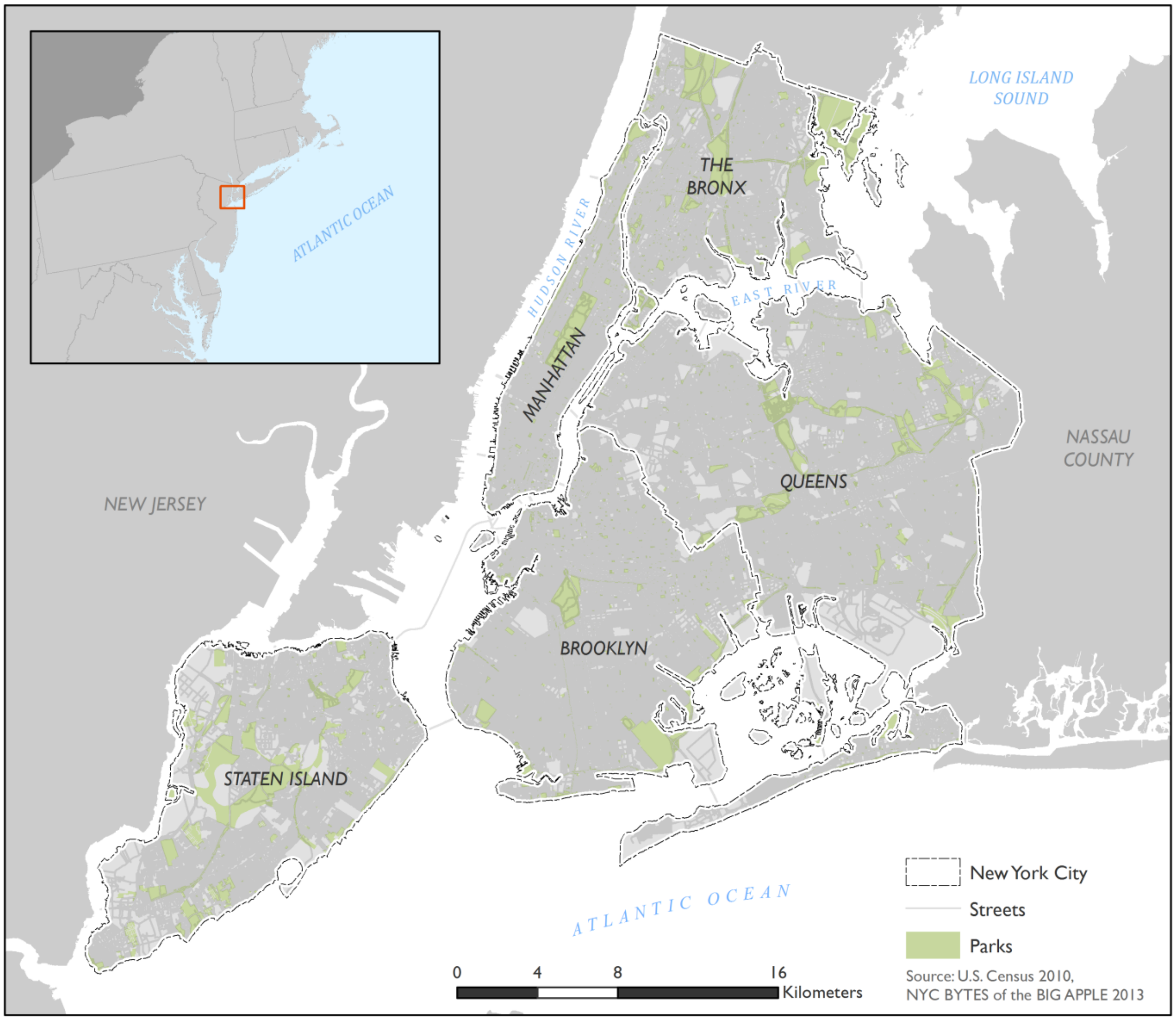
The IPCC (2007) predicts global sea levels to rise between 0.18 and 0.59m by 2100, although more recent studies provide evidence for a rise of over a meter in the same period of time (Rahmstorf et al. 2007; U.S. Army Corps of Engineers 2011; Scientific Committee on Antarctic Research 2009; Arctic Monitoring and Assessment Programme 2011; Vellinga et al. 2009). Rising sea levels are associated with more frequent acute weather events, such as typhoons and hurricanes, storm surges, and higher levels of precipitation (Balk et al. 2009; FitzGerald et al. 2008). Additionally, there is a high degree of uncertainty associated with these predictions, making planning for sea level rise and more extreme weather events challenging (Meo 1990).

Sea level rise poses a serious threat and is already affecting coastal areas (Williams 2013). Rising sea levels result in inundation and coastal erosion and may substantially alter beaches and barrier islands (London and Volonte 1991; FitzGerald et al., 2008). The changing topography and more frequent extreme weather events will, in turn, impact coastal communities and their ability to weather storms.

The global coastal population's vulnerability to sea level rise is well documented. The United States ranked eighth in the world in terms of population living in low elevation coastal zones, areas characterized as less than 10 meters above sea level (McGranahan et al. 2007). More specifically, 8 million people live in vulnerable coastal areas in the country, while 3.7 million people live within one vertical meter of the local high tide line (Crowell et al. 2010; Strauss et al. 2012). The concentration of cities on the coasts represents a problem not only in terms of vulnerable populations, but also places trillions of dollars in assets at risk (Hanson et al. 2011). With so much social and political capital located in vulnerable areas, the United States needs to identify how to best adapt to potential risks posed by a changing climate.

Study Area

Figure 1. Study Area



New York City represents the extent of the study area in this paper (Fig. 1). In a study considering socio-economic and climate changes, Hanson et al. (2011) identified New York City as one of the most vulnerable port cities in the world to climate extremes, while Colle et al. (2008) conclude it is especially vulnerable to storm surges and flooding. Its vulnerability is compounded by its location within the "northeast hotspot" (Sallenger et al. 2010); sea levels along the North American Atlantic coast rose three to four times faster between 1950 and 2009 than the global average. The northeastern sea level rise rate will continue to outpace that of the global as average temperatures continue to increase. While global sea levels are projected to rise by 0.35 meters, it is expected that sea levels in the New York City region will rise 0.23 to 1.07 meters by 2100 (IPCC 2007; Bloomfield 1999). According to the New York City Panel on Climate Change (2013), middle range estimates place sea level rise are 0.10 to 0.20 meters in the 2020s and 0.28 to 0.61 meters in the 2050s.

In the fall of 2012, Hurricane Sandy served as a reminder to the area's vulnerability. The storm's aftermath presented the region with many challenges, as is the case with most natural disasters of comparable scale. After such an extreme event, infrastructure is wrecked, business activity is interrupted, and people migrate away from the impacted area (Ewing et al. 2007; Thompson 2009). The National Hurricane Center estimates Hurricane Sandy resulted in over $50 billion in damage (NOAA 2013).

As the global climate changes, it becomes more imperative to identify how and where to focus adaptation measures in order to minimize impacts (Williams 2013). Ewing and others (2007, p. 315) acknowledged that, "the challenge is to identify and adopt strategies that allow a region to reduce the disruption and promote recovery that improves the quality of life for all segments of the population." New York City is part of a broader vulnerable region, but given data availability, this study will only focus on the area within the city's limits.

Development Patterns and Policies

Before performing a suitability analysis, it is important to consider current and anticipated development patterns within the study area. While this analysis will consider environmental factors, the natural environment is shaped by the policies governing development. New York City is intensifying development along certain portions of the waterfront, while also restoring the ecological integrity of other areas. There has been continuous redevelopment along the waterfront (Buttenwieser 1999). With *PlaNYC: A Greener, Greater New York,* the Bloomberg administration accelerated waterfront redevelopment but also cited as a priority the city's improved resilience to a changing climate (City of New York 2011). The study *Urban Waterfront Adaptive Strategies* identifies a variety of approaches for the City to take in adapting to threats associated with climate change and promoting coastal climate resilience (NYC Department of City Planning 2013b). After Hurricane Sandy, the City unveiled the plan *A Stronger, More Resilient New York*, which outlines its approach to rebuilding post-Sandy and preventing another event comparable to Sandy from happening again (NYC Department of City Planning 2013a). All of these plans provide the City with a framework for waterfront development.

While development has intensified along the Brooklyn and Manhattan waterfronts, there have also been efforts to restore certain natural areas' ecological capacities in vulnerable areas. In the case of Freshkills Park on Staten Island, a park was created on top of an old landfill in an area identified in this analysis for its poor suitability (City of New York 2011). The Department of Parks and Recreation is also developing a plan for the further restoration of the Rockaways. Both of these efforts "provide buffer capacity for protecting waterfronts and the City against (future) flood risk" (Aerts and Botzen 2011, p. 45).

Recent changes in flood zoning policy will also inform future development. The Federal Emergency Management Agency (FEMA) is expanding the flood zones designated in Flood Insurance Rate Maps (FIRMs) and flood elevations. This is in addition to the changes in the New York State Building Code adopted in January 2013 requiring building protections for one to two feet higher than FEMA flood levels (NYC City Planning Commission 2013). As a result of changes in the federal and state policy, more buildings will be designated within the flood zone and required to have the appropriate protections. In response, the New York City Council passed the Flood Resilience Zoning Text Amendment to allow for building construction based on the most recent FIRMs (NYC City Planning Commission 2013; Aerts and Botzen 2011). These federal, state and local policies are informing development in flood zones, and it is within this context that I will consider the future development suitability in New York City.

Suitability analysis: an overview

This study will use a land suitability analysis to identify areas best suited for urbanization with a particular interest as to how suitability change when considering rising sea levels. If in determining future land use decision makers employ suitability analysis, then it is logical to consider future conditions. The results of a suitability analysis today may be different from those fifty years from now simply because the processes which regulate the criteria considered in a suitability analysis are dynamic.

A GIS-based land suitability analysis can be used to determine land uses most appropriate for a given area based on these processes and other relevant criteria. The premise of a suitability analysis is that an area's suitable land use is a function of natural processes and the built environment. Ian McHarg wrote that, "…any place is the sum of historical, physical, and biological processes," and he used that principle to develop the ecological inventory process through mapping overlay technique (1969, p. 104). Since the publication of McHarg's *Design with Nature*, methods for suitability analysis have evolved and today it is used for a variety of applications, including but not limited to: geological favorability, agriculture, site selection, habitat for animal and plant species, and environmental impact assessment (Malczewski 2004).

There are three general methods to perform a suitability analysis: computer-assisted overlay mapping, multi-criteria evaluation, and artificial intelligence (Chakma 2014; Malczewski 2004). Elements of the three methods are often blended in practice, and some form of overlay mapping is used in most methods. Computer-assisted overlay mapping is the next step in the evolution of the manual overlay mapping method. It is commonly applied through Boolean operation and weighted linear combination (WLC). This method is easy to implement in a GIS environment, but is often used without a full understanding of the underlying assumptions (the weights assigned to each criteria). The overlay mapping method is insufficient by itself because it assumes all attributes to be linearly independent (Hopkins 1977). Boolean operations and WLC may oversimplify land use planning by excluding any consideration for value judgments and only focusing on facts. Value judgments can be incorporated through multi-criteria decision making (MCDM) methods.

There has been substantial research on the topic of the integration between GIS and MCDM and is a widespread approach to suitability analysis (Yu et al. 2009; Malczewski 2006). MCDM methods apply both spatial and non-spatial data to decision making and are divided between multi-objective methods and multi-attribute methods (Malczewski 2004). Multiattribute methods are data-oriented, whereas multi-objective methods are based on mathematical programming. One of the most significant advantages associated with multi-attribute methods is their ability to incorporate both qualitative and quantitative criteria (Greene et al. 2011). As a result of their relative ease, multi-attribute methods are more commonly used in solving land-suitability problems. The analytical hierarchy process (AHP), developed by Saaty (1980), is a widely used multi-attribute technique used to obtain the weights for each suitability criteria. It is regularly integrated into GIS-based suitability analysis because the AHP makes it relatively easy to derive criteria's weights, one of the problems associated with MCDM (Saaty 1980; Saaty and Vargas 1991).

There are a number of problems associated with MCDM methods. First, multi-attribute methods do not solve the problem of assumed linearity among attributes that also plagues the overlay method. Second, the MCDM method assumes the input data to be accurate when in reality the data will have some associated degree of inaccuracy and uncertainty. Using a multi-criteria evaluation method in land suitability analysis has the potential to overlook the complexities of the systems underlying land use planning (Yu et al. 2011). While the AHP is a widely used approach, there are other methods that might produce different results, and the inconsistency between methods is an additional problem with MCDM.

Finally, artificial intelligence (AI) methods address data inaccuracies and uncertainties by allowing for vagueness and uncertainty (Cheng et al. 2001). AI methods include fuzzy logic techniques, neural networks, evolutionary algorithms, and cellular automata. Fuzzy logic is an AI method particularly appropriate for addressing the uncertainty of spatial boundaries (Murgante & Las Casas 2004). In conventional techniques the boundaries are to a certain extent arbitrary, but fuzzy logic techniques treat boundaries as a function instead of a binary. While fuzzy logic has fewer limitations than conventional methods, its difficulty lies in establishing membership functions. AI methods are generally considered more nuanced than alternative methods, but their complexity limits their application and renders them inaccessible to many city planners and policymakers (Malczewski 2004). Additionally, they are less easily integrated into a GIS environment and many AI methods' internal processes are hidden. This lack of transparency makes their results less likely to be considered by decision makers (O'Sullivan and Unwin 2003).

This study will apply MCDM methods through the AHP and weighted linear combination to determine how sea level rise will influence land uses. MCDM methods are preferred because of their ability to incorporate value judgments and because they are able to consider both qualitative and quantitative criteria (Malczewski 2006; Greene et al. 2011). The AHP will be used to calculate criteria weights because of its ability to objectively compare and rank subjective criteria with inconsistent scales (Saaty and Vargas 2001). The AHP is also preferred because it provides a way to quantify the consistency of the value judgments through the consistency ratio.

Methodology

Evaluation Criteria

Evaluation criteria should be chosen so that they offer a comprehensive understanding of the problem, and were selected based on a review of similar studies (Saaty and Vargas 2001; Malczewski 1999; Chen et al. 2009). The following criteria will be used: land cover; elevation; slope; rock type; distance to coastline; and areas inundated from sea level rise (Table 1, Fig. 2).

Table 1. Data Sources

Evaluation Criteria	*Source*	*Citation*
Land Cover	University of Vermont Spatial Analysis Laboratory & New York City Urban Field Station (2010)	Rojas, Pino & Jacque 2013; Pathan et al. 1992; Chakma 2013; Doygun et al. 2008; Dong et al. 2008; Reshmidevi et al. 2009; Yu et al. 2011
Elevation	US Geological Survey (2013)	Chakma 2013; Dong et al. 2008; Reshmidevi et al. 2009
Slope	Derived from DEM (USGS 2013).	Joerin et al. 2001; Davidson et al. 1994; Aly et al. 2005; Pourebrahim et. Al. 2011
Rock Type	USGS (2008)	Davidson et al. 1994; Yu et al. 2009; Pathan et al. 1992; Reshmidevi et al. 2009
Distance to coastline	NYC Department of City Planning (2012)	
Inundated areas	USGS (2013); NPCC (2013)	

Modeling Inundation

Inundated areas will be modeled by applying sea-level rise projections from the NYC Panel on Climate Change (2013) to the bathtub model approach (Poulter and Haplin 2008; Gesch 2009). This method assumes that sea-level rise will be evenly distributed and sea levels will rise as if filling up a bathtub. This is an elementary approach, as sea level rise will not be uniform across a region and will be influenced by changing landscape morphology and ecological feedbacks (Poulter and Haplin 2008).

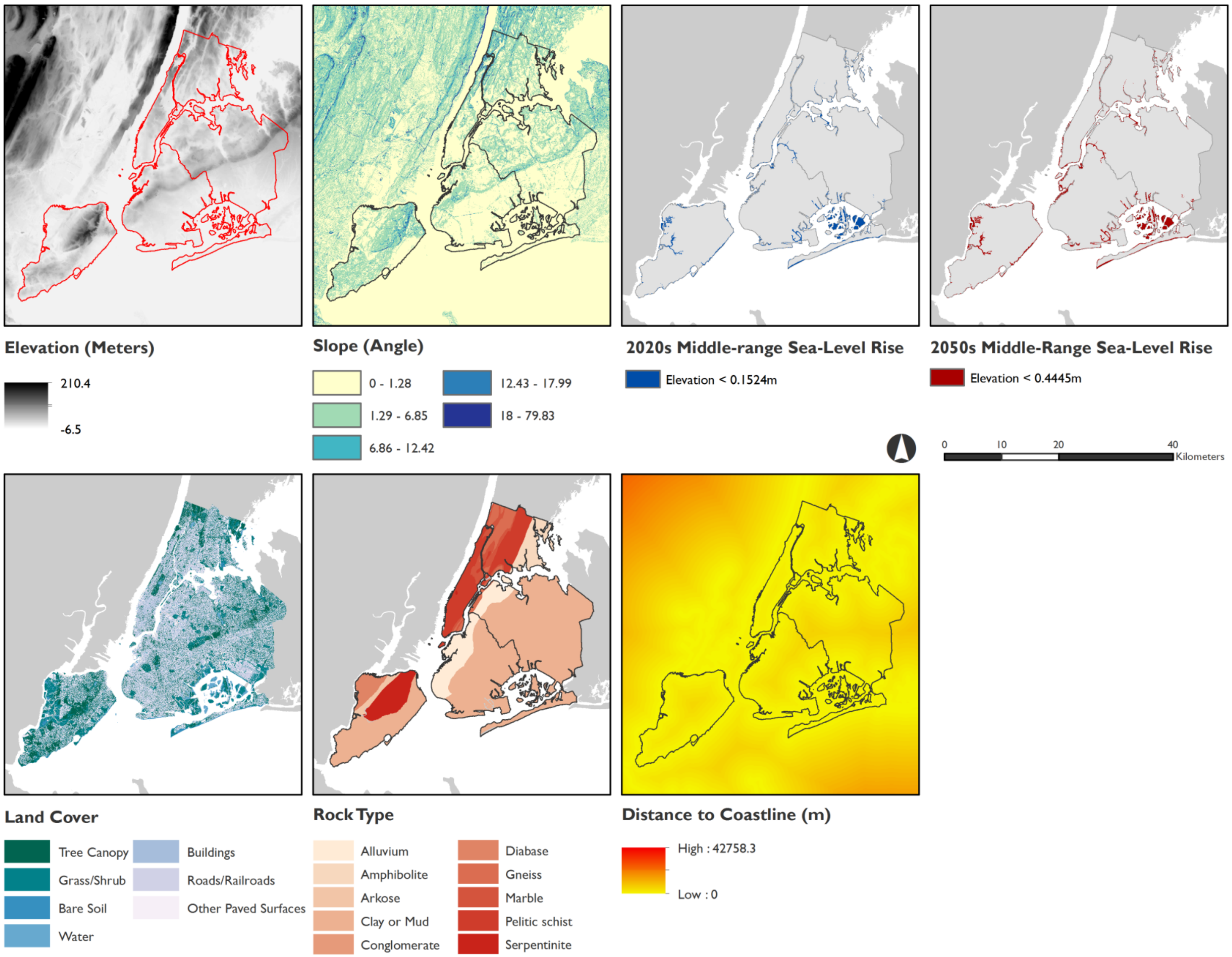
A land cell is considered inundated if it meets two conditions: its elevation is lower than that of the considered sea level rise projection, and it is connected to the ocean via a continuous path of other inundated cells (Gesch 2009; Poulter and Halpin 2007; Bales et al. 2007). The second condition considers the hydrological connectivity of the land cell; otherwise, isolated inland land cells meeting the elevation threshold would be included. The averages of the middle range estimates are used in this analysis (Table 2).

Table 2. Sea Level Rise Projections

Baseline (2000-2004) 0 meters	Middle range (25th to 75th percentile)	Average
2020s	0.1016m to 0.2032m	0.1524m
2050s	0.2794m to 0.6096m	0.4445m

Source: NPCC (2013)

Figure 2. Criteria



Analytical Hierarchy Process and Weighted Linear Combination

The criteria considered are not measured according to the same scale, and land cover and lithology are categorical. In order to combine criteria, the different scales are reconciled by establishing priorities through pairwise comparisons. The AHP uses a "fundamental scale" of 1-9; it is fundamental in that has been evaluated for effectiveness and is based on stimulus-response theory (Saaty and Vargas 2001; Saaty 2001). The values of 1-9 (or, alternatively, their inverses) are assigned to each pair of criteria to establish their importance relative to one another. One refers to the pair of criteria being of equal importance, while 9 refers to the criterion being of extreme importance relative to the other criterion being compared. The resultant inverse matrix (Table 3) details each pairwise comparison and their relative priorities.

An advantage of the pairwise method is that only two criteria are considered at a time, eliminating the need to rank all of the criteria relative to each other at once (Malczewski 1999). Additionally, pairwise comparisons are better suited to situations in which "the accuracy and theoretical foundations are the main concerns (Malczewski 1999, p. 189)."

Table 3. Pairwise Comparison Matrix

	E	*S*	*R*	*L*	*SLR*	*D*
Elevation *E*	1					
Slope *S*	⅓	1				
Rock Type *R*	1/5	1/5	1			
Land Cover *L*	2	2	3	1		
Inundated Area *SLR*	2	5	5	5	1	
Distance to coast *D*	1/5	1/5	1/5	1/5	1/5	1

Table 4. Normalized Pairwise Comparison

	E	*S*	*R*	*L*	*SLR*	*D*
Elevation *E*	0.174	0.263	0.197	0.045	0.217	0.192
Slope *S*	0.058	0.088	0.197	0.068	0.087	0.192
Rock Type *R*	0.035	0.018	0.066	0.045	0.087	0.192
Land Cover *L*	0.349	0.175	0.197	0.136	0.087	0.192
Inundated Area *SLR*	0.349	0.439	0.329	0.679	0.435	0.192
Distance to coast *D*	0.035	0.018	0.013	0.027	0.087	0.038

The criterion weights are derived from the normalized pairwise comparison matrix (Table 4). The elements of the Eigenvector that corresponds to the maximum Eigenvalue of the normalized pairwise comparison matrix represent the criteria weights (Saaty and Vargas 2001; Feizizadeh and Blaschke 2012). An Eigenvector v is a nonzero vector that when multiplied by a matrix M results in a vector that is parallel to v or equal to zero: $Mv = \lambda v$, where λ is the Eigenvalue, a scalar, associated with a given Eigenvector (Kuttler 2012).

Each criterion weight w_i is the sum of a column in the normalized matrix divided by the sum of all of the normalized matrix elements b_{ij}. The weights are calculated as such:

$$w_i = \frac{\sum_{j=1}^{n} b_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} b_{ij}}, i, j, = 1, 2, 3, \ldots, n$$

The consistencies of priorities established in the pairwise comparison matrix are evaluated through the consistency ratio. A pairwise comparison matrix is considered consistent if the consistency ratio (CR) is less than 0.10 while a value greater than 0.10 suggests that the value judgments are inconsistent with each other and should be reevaluated (Saaty and Vargas 2001).

The CR is calculated as:

$$CR = \frac{CI}{RI}$$

where CI is is the Consistency Index and RI is the Random Index, the consistency index of a completely random comparison matrix. The RI associated with 6 criteria is 1.24. The consistency index (CI) is found as:

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

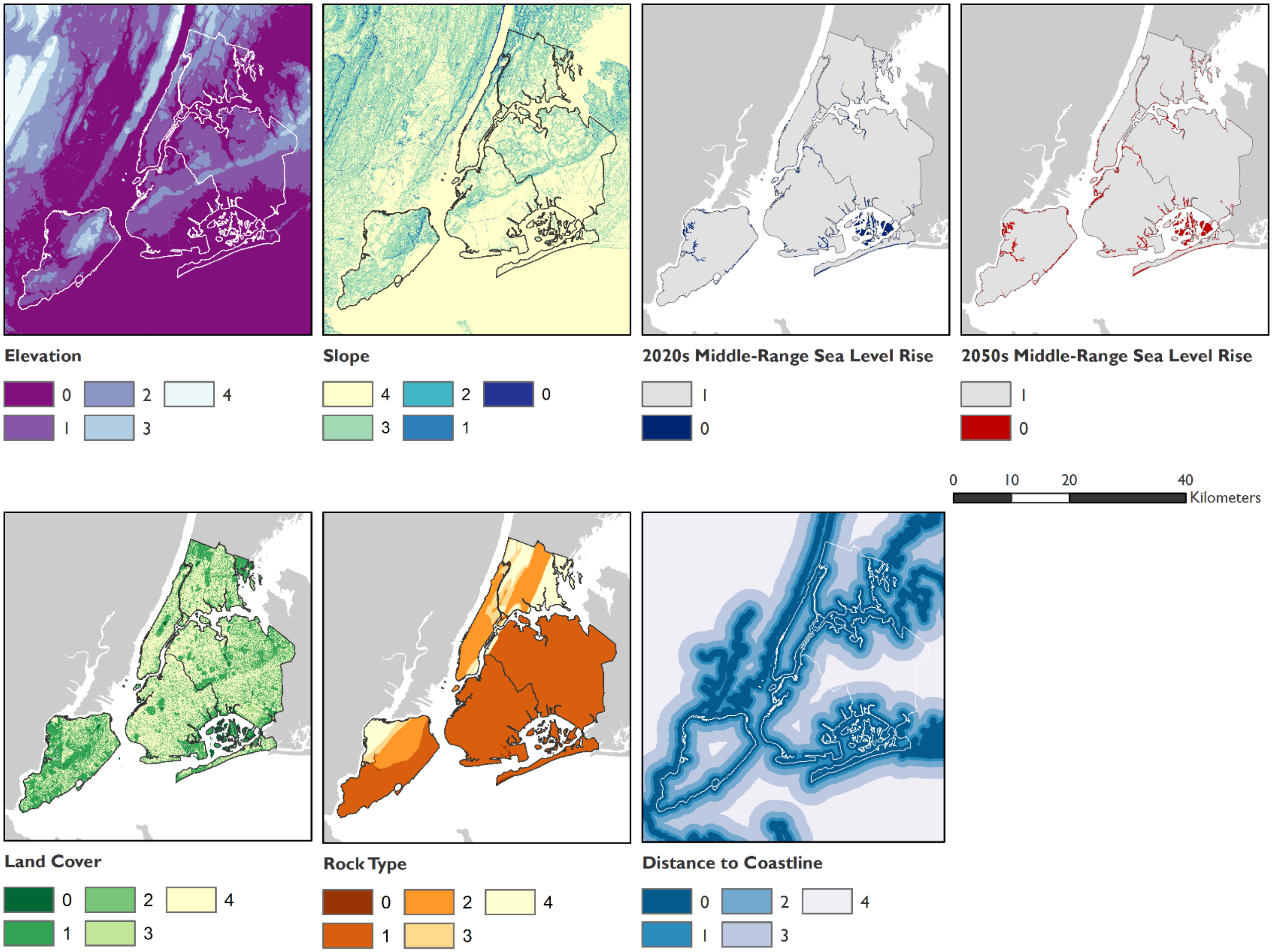
where n is the number of criteria, and λ_{max} is the Eigenvector associated with the comparison matrix's largest Eigenvalue. The consistency ratio associated with this pairwise comparison matrix is 0.09; the pairwise comparisons are consistent and the resulting weights are appropriate for a weighted linear combination.

In order to perform a weighted linear combination, the criteria's heterogeneous measurement scales and units were reconciled with each other by reclassifying their values (Greene et al. 2011; Malczewski 2004). The criteria were reclassified into a scale of 0 to 4, with 4 representing the most suitable alternative (Fig 3; Table 5). The divisions of a criterion's classes were established at the natural breaks according to the Jenks Method, which minimizes statistical variation within each class (Baz et al. 2009; Jenks 1977). As land cover and rock type are qualitative criteria, they were reclassified according to standards in the literature (Afrouz 1992; Djuric et al. 2013). Sea level rise was only reclassified into a binary scale, with 1 representing no inundation and 0 representing inundation.

Table 5. Criteria Classes and Weighting

Criteria	Weight	Classes		Reclassified
Distance to coastline (m)	0.04	Near	0 -500	0
		Moderately Near	500 - 1,000	1
		Far	1,000 - 2,000	2
		Very far	2,000 - 4,000	3
		Distant	> 4000	4
Slope (degrees)	0.12	≤ 1.13		4
		1.13 - 4.54		3
		4.54 - 10.77		2
		10.77 - 22.97		1
		≥ 22.97		0
Elevation (m)	0.18	Very High	110.04 - 210.40	4
		High	61.57 - 110.04	3
		Medium	29.25 - 61.57	2
		Low	7.13 - 29.25	1
		Very Low	-6.4 - 7.13	0
Land cover	0.19	Built-up Area	Buildings, Paved surfaces	4
		Suitable	Roads/railroads	3
		Conditionally Suitable	Bare soil	2
		Unsuitable	Tree canopy, grass/shrub	1
		Water	Water	0
Rock Type	0.07	Most suitable	Gneiss, diabase, amphibolite	4
		Suitable	Marble, arkose, conglomerate	3
		Moderately suitable	Pelitic schist, serpentinite	2
		Least suitable	Clay or mud, alluvium, silt	1
		Unsuitable	Water	0
Inundated Areas	0.4	Inundated	2020s - Elevation > 0.1524m	0
			2050s - Elevation > 0.3062m	0
		Not		1

Fig. 3. Reclassified Criteria. Except for sea level rise, the criteria ere reclassified into a scale of 0-4. Sea level rise which was assigned a value of 0 or 1. See Table 6 for how the values correspond to the criteria's unclassified data.



A weighted linear combination produced the final suitability score. The reclassified criteria were weighted according to the weights generated by the AHP and then summed using the map algebra tool in ArcGIS 10.1. The resultant number is a numeric representation of the land cell's suitability. In order to make the results more easily communicated, the final suitability scores were then reclassified at their natural breaks according the Jenks Method. The final suitability classes include: *Most Suitable, Suitable, Conditionally Suitable, Moderately Suitable*, and *Not Suitable*.

Results

Suitability maps for the baseline conditions and sea level rise projections for the 2020s and 2050s were created (Fig. 4; Table 6; Table 7). The area classified as *Not Suitable* increased for both the 2020s and 2050s, while *Conditionally Suitable, Suitable, and Most Suitable* decreased for both time periods. The *Moderately Suitable* areas decreased between the baseline conditions and the 2020s, but slightly increased between the 2020s and the 2050s.

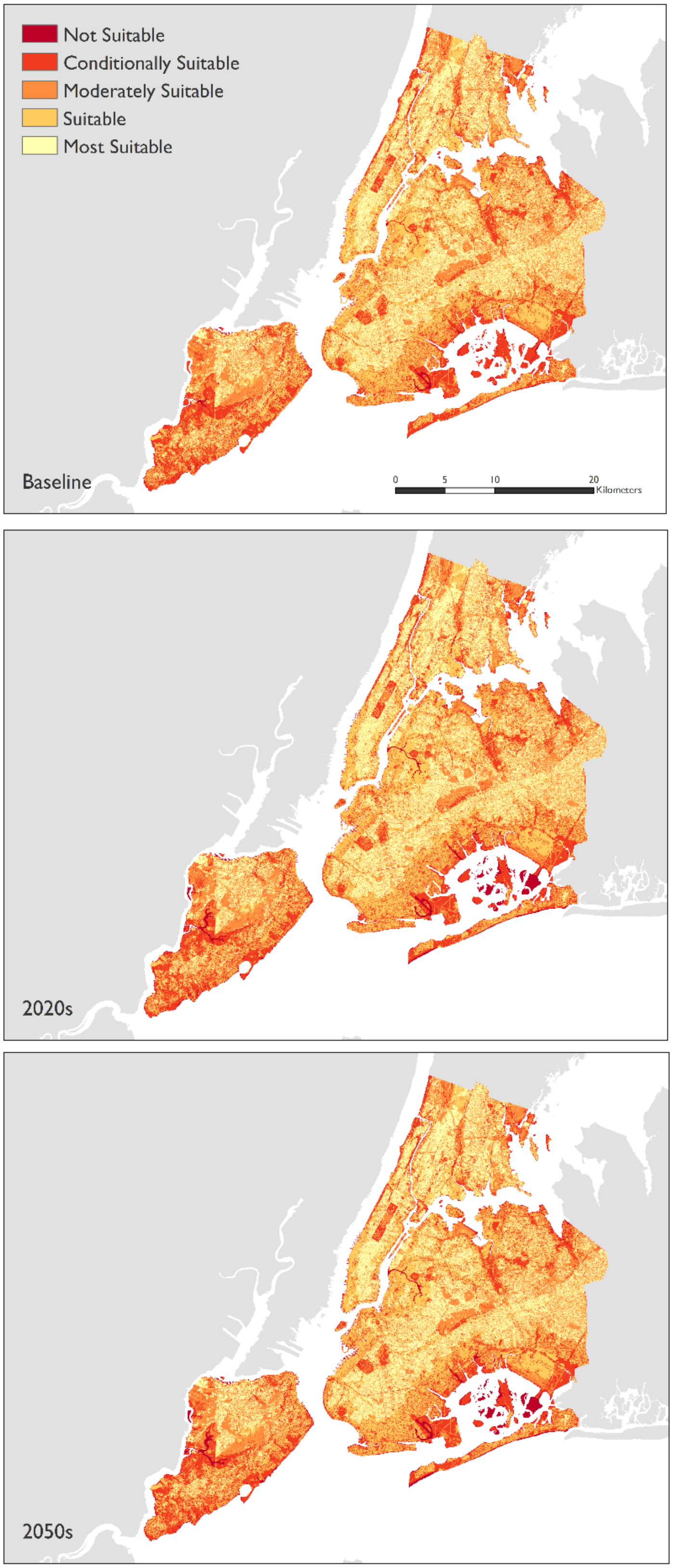
Table 6. Suitability Classes by Area (Hectares)

	Baseline	2020s	2050s
Not Suitable	834.08	1864.39	2060.34
Conditionally Suitable	16724.10	15892.24	15841.35
Moderately Suitable	17436.94	17387.34	17442.31
Suitable	23674.59	23541.62	23350.79
Most Suitable	19491.96	19477.14	19468.06
Total	*78161.67*	*78162.73*	*78162.85*

Table 7. Percent Change by Area

	Base/2020	Base/2050	2020/2050
Not Suitable	123.53%	147.02%	10.51%
Conditionally Suitable	-4.98%	-5.28%	-0.32%
Moderately Suitable	-0.28%	0.03%	0.32%
Suitable	-0.56%	-1.37%	-0.81%
Most Suitable	-0.08%	-0.12%	-0.05%

Fig. 4. Suitability Analysis Results



The areas with the most visible changes in suitability are eastern Staten Island (Fig. 6) and the southern portions of Brooklyn and Queens, particularly Rockaway Peninsula and Jamaica Bay (Fig. 5). Staten Island and Rockaway Peninsula act as New York City's initial barriers to storms moving in from the Atlantic Ocean. In the Rockaways, the peninsula separating Jamaica Bay from the Atlantic Ocean, there was a significant decrease in suitable areas between the baseline conditions and the 2020s. There was little significant change between the 2020s and 2050s for the Rockaways. On Staten Island, the *Not Suitable* area increased most significantly on the western edge bordering New Jersey in Freshkills Park along with the eastern side adjacent to New York Bay. The impact of sea level rise on Staten Island's eastern side is likely understated in this analysis because of the risk of storm surges

Fig. 5. Rockaway Peninsula and Jamaica Bay

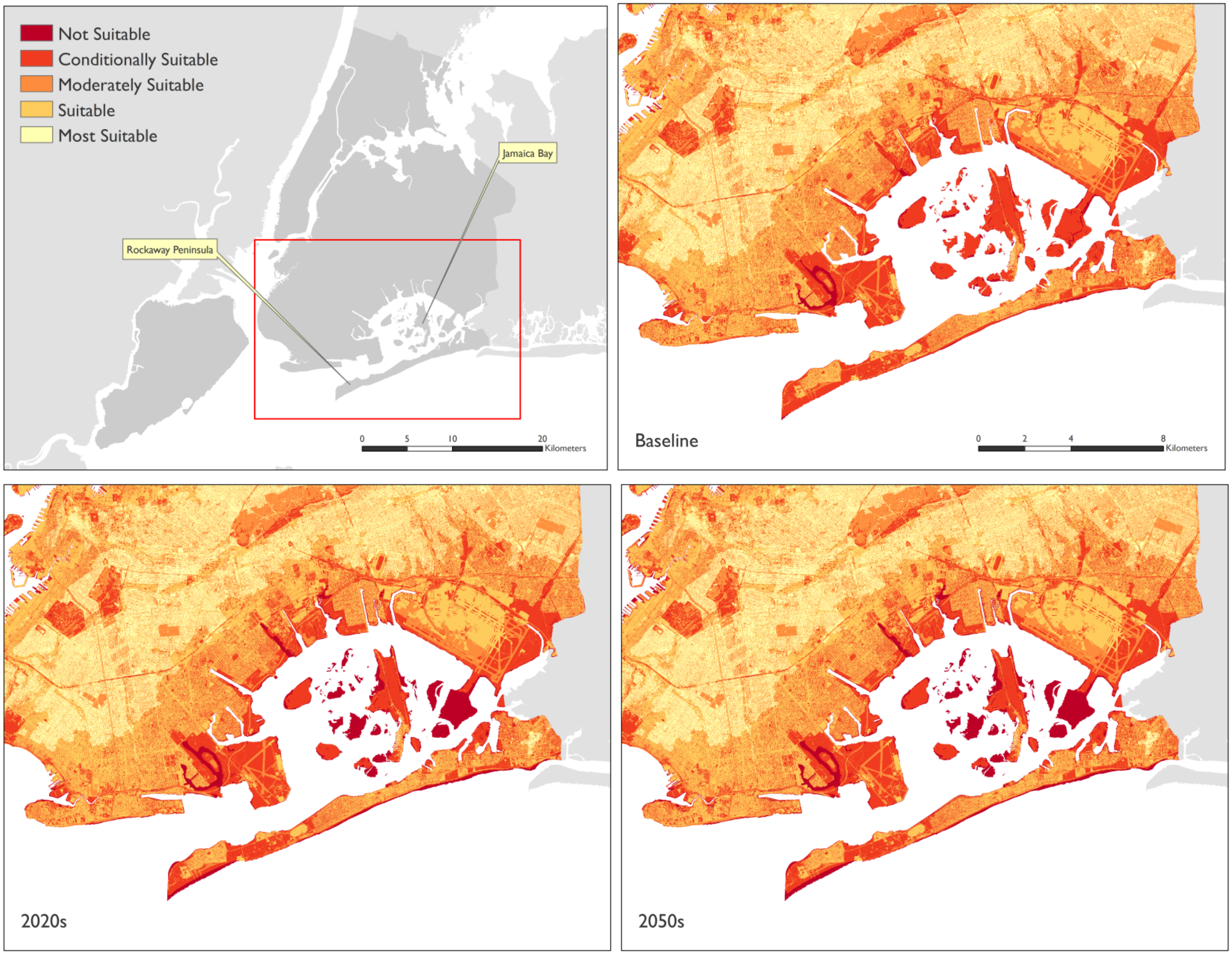
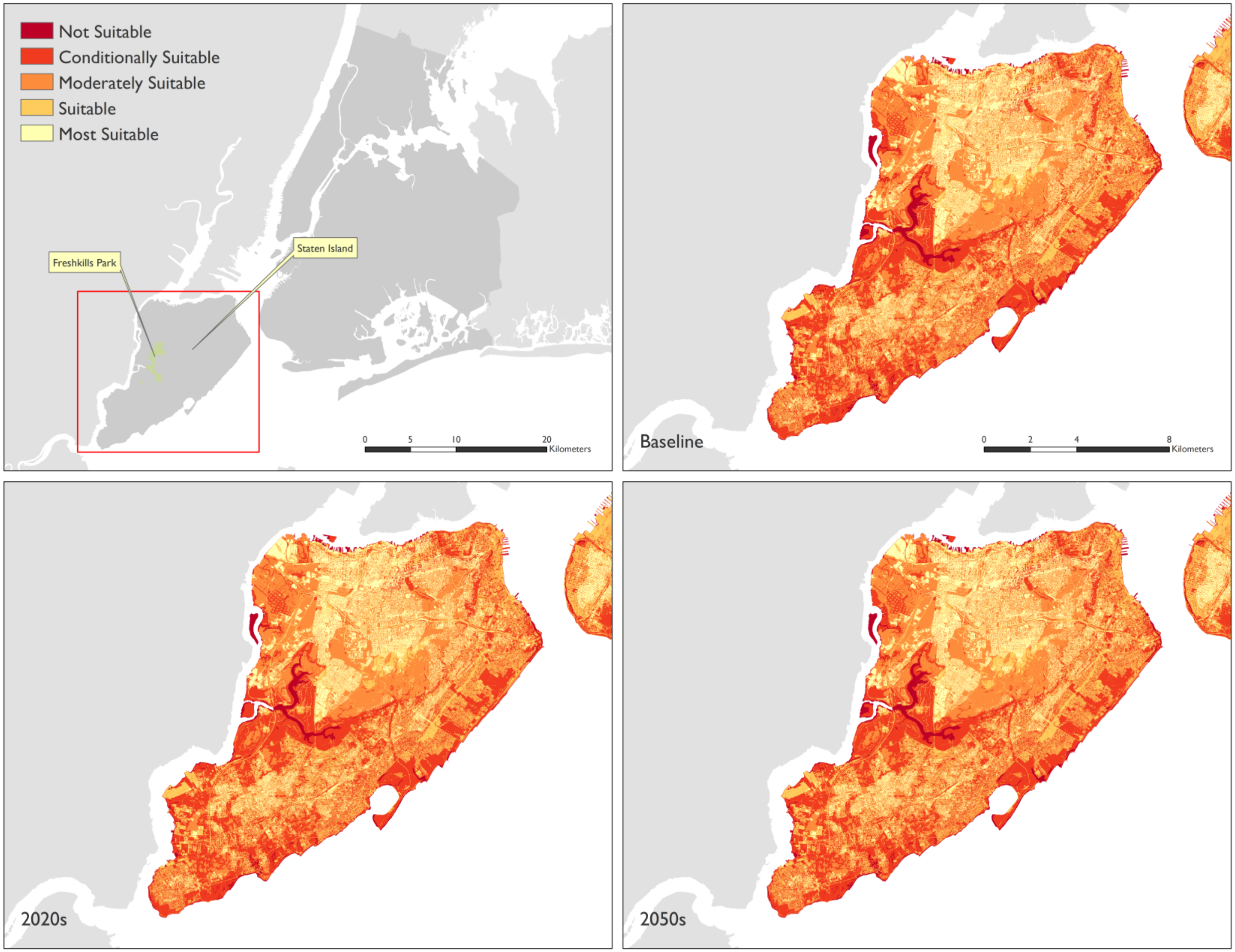


Fig. 6. Staten Island



Discussion

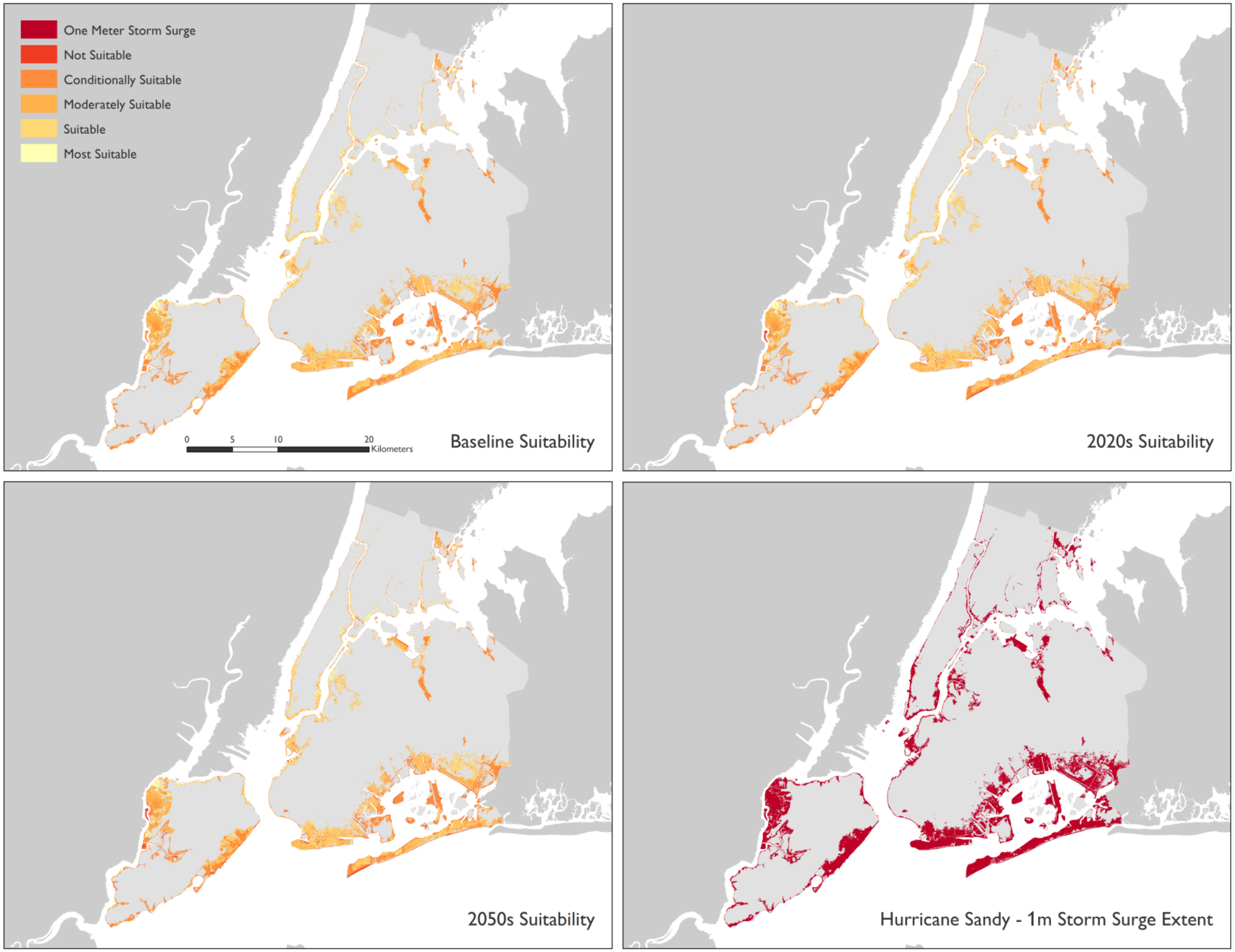
We can compare the areas affected by Hurricane Sandy with the results of this suitability analysis (Fig. 7; Table 8). This analysis characterizes the extent of the one meter storm surge during Hurricane Sandy as predominantly *Conditionally Suitable, Moderately Suitable*, and *Suitable*. The storm surge extent has a larger area classified as *Not Suitable* when compared with the city as a whole for both the 2020s and 2050s suitability analysis. For the entire city, the area classified as *Not Suitable* was 2.38% and 2.64% for the 2020s and 2050s projections respectively. However, within the storm surge extent, it is 3.66% for the 2020s and 4.81% for the 2050s.

Table 8. Comparison of Suitability Analysis Results with Hurricane Sandy 1m Storm Surge Extent

	Area (Hectares)		Percentage of Storm Surge Extent Area	
	2020s	2050s	2020s	2050s
Not Suitable	436.088	573.06	3.66%	4.81%
Conditionally Suitable	4649.34	4625.62	38.99%	38.79%
Moderately Suitable	2416.15	2463.07	20.26%	20.65%
Suitable	4004.78	3852.14	33.58%	32.30%
Most Suitable	419.11	411.67	3.51%	3.45%

That this suitability analysis characterizes the Hurricane Sandy storm surge extent as less suitable than the rest of the city suggests this analysis provides results that reflect current vulnerable areas.

Fig. 7. Comparison of Suitability Analysis with Hurricane Sandy



There are several limitations to this analysis. It is dependent on the accuracy of sea level rise projections, and there is uncertainty associated with all climate models. The bathtub model assumes that sea-level rise will be uniform across the region, when it will really be subject to more local conditions. A more accurate model of sea level rise would account for bathymetry, tidal patterns, and coastal geomorphology, among other factors. The distance to the shoreline was used in combination with inundated areas as a proxy for flood and storm surge risk. Incorporating floodplain areas and giving weight to areas more likely to flood would further improve this analysis.

The biggest limitation with this suitability analysis is that it fails to fully consider the relation between sea level rise and the adjacent areas. The only changes in suitability came in the inundated areas, but rising sea levels and a changing coastline will have an impact beyond them. For example, there was a limited change in suitability in Lower Manhattan. However, based on previous flooding events, it's evident that this area is much less suitable for development than this analysis suggests. In future analysis, this disconnected could be remedied by incorporating fuzzy logic techniques. Doing such would allow the inundated areas to have more of an influence on the adjacent areas, whereas in this suitability analysis they were to a certain degree treated independently.

One of the goals of this analysis was to examine how a changing condition – sea level rise – impacts the suitability for future development. It assumes that the other conditions are static; in reality they are dynamic and will not be the same in the observed time span. Criteria are subject to both environmental and human forces. Unless there are significant human impacts, the rock type, elevation, and slope will be largely the same given they change on a geologic time scale. Land cover is the most dynamic criteria and is subject to development patterns, and therefore it is important to consider the results of this analysis within the context of current and future patterns of development. In New York City, there has been a focus on waterfront development, but this analysis does not consider how that development is adapted to withstand environmental factors. This analysis could be improved by incorporating more detailed information about the type of protections and adaptations used in a given building.

Another goal of this analysis was to provide a potential tool to urban planners, developers, and policymakers regarding future development. While some areas are clearly dominated by a single suitability class, other areas are a mix of two or three classes. These mixed areas would make it difficult to translate the analysis's results to real-world applications.

Conclusion

In this paper, I conducted a suitability analysis for development in New York City and examined how sea level rise will affect areas suitable for development. It expanded on McHarg's (1969) original analysis of Staten Island and subsequent research on GIS-based suitability analysis (Malczewski 2004; Feizizadeh & Blaschke 2013). The criteria used to assess the area's suitability included: elevation, slope, land cover, rock type, distance to shoreline, and areas inundated by rising sea levels. The weights of each criterion were produced using the AHP. After reclassifying the criteria into a scale of 0 to 4 according to the Jenks Method, they were combined through a weighted linear combination

Sea-level rise will dramatically increase the areas not suitable for development, but over fifty percent of the city's area will still be characterized as *Most Suitable* and *Suitable* for both the 2020s and 2050s time periods. In particular, Eastern Staten Island and the southern shore of Brooklyn and Queens are projected to become less suitable for development.

This analysis provides policymakers and urban planning professionals with a tool for examining the suitability of an area for development that is rooted in the area's natural and man-made landscape. The methodology used is not unique to New York City, and can therefore be adapted to other coastal areas. It can inform future land use decisions and help aid in risk management and prevention. Incorporating a temporal element (sea level rise) partially removed the assumption that conditions are static; incorporating other temporal elements would further strengthen this analysis. Additionally, improving the modeling techniques used for sea-level rise and considering how the criteria aside from sea level rise will make this analysis more applicable.

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